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Energy models for demand forecasting—A review

L. Suganthi[a,*], Anand A. Samuel[b]

[a] Department of Management Studies, Anna University, Chennai 600025, India
[b] VIT University, Vellore 632014, India

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ABSTRACT

Energy is vital for sustainable development of any nation – be it social, economic or environment. In the past decade energy consumption has increased exponentially globally. Energy management is crucial for the future economic prosperity and environmental security. Energy is linked to industrial production, agricultural output, health, access to water, population, education, quality of life, etc. Energy demand management is required for proper allocation of the available resources. During the last decade several new techniques are being used for energy demand management to accurately predict the future energy needs. In this paper an attempt is made to review the various energy demand forecasting models. Traditional methods such as time series, regression, econometric, ARIMA as well as soft computing techniques such as fuzzy logic, genetic algorithm, and neural networks are being extensively used for demand side management. Support vector regression, ant colony and particle swarm optimization are new techniques being adopted for energy demand forecasting. Bottom up models such as MARKAL and LEAP are also being used at the national and regional level for energy demand management.

Contents

* Corresponding author. Mobile: +91 98412 44331.
E-mail address: suganthi_au@yahoo.com (L. Suganthi).

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1. Introduction

The twentieth century witnessed a transition from coal based to petroleum based resources. With the advent of industrialization and globalization, the demand for energy has increased exponentially. Fossil fuels in the form of coal, oil and natural gas comprise 80% of the world's energy use. It is predicted that if the current global energy consumption pattern continues, the world energy consumption will increase by over 50% before 2030 [1]. In this scenario, protection of the environment becomes very vital for sustainable living. Relevant factors of the environment include food, water, energy, natural resources, etc. Among these, energy is the most important factor.

Energy is essential for the functioning of all activities be it a developed or developing nation. It is estimated that industrial energy use in developing countries is around 45–50% of the total commercial energy consumption. Yet at the same time, large scale production and consumption of energy causes degradation of the environment. Also commercial energy resources are also non renewable in nature. This has led policy makers and industrialists to identify efficient means of energy utilization and also look at alternate sources of energy. In this backdrop, utilization of renewable energy is slowly gaining momentum across the globe.

Energy demand management is becoming an important issue since the future world is dependent on today's decision. Managing the energy resources in an optimal manner has become imperative among energy planners and policy makers. It is becoming mandatory that the commercial and renewable sources of energy be understood in its totality – quality, availability and environmental effects. In recent times, with climatic conditions going for drastic reversals, the attention has shifted to the utilization of renewable energy sources. The renewable energy sources have been established to be sustainable, nature friendly, non-polluting and renewable. An integrated energy management approach is essential for the sustainable development of any country.

2. Energy demand management

Energy demand management involves effective utilization of the energy resources, reliability in supply, efficient management of energy resources, energy conservation, combined heat and power systems, renewable energy systems, integrated energy systems, independent power delivery systems, etc. Demand management has to consider a series of options be it technical, organisation and behavioural solutions so as to decrease the energy consumption and demand. Cost effective options, commercially viable alternatives and environmental friendly solutions need to be explored. Demand management consists of planning, implementing, and monitoring activities of energy utilization that are designed to encourage consumers to modify their level and pattern of energy usage.

Demand side management has changed focus during the nineties with the several changes happening across the globe – technological advancements, communication breakthroughs, improvements in manufacturing processes resulting in better quality at lower costs. The emphasis of demand side management had shifted from residential load management to commercial and industrial demand management. Demand side management promotes energy efficiency for sustainable development.

Energy demand is found to be closely linked to energy price, GDP, population to name a few. Energy demand management should help in achieving self sufficiency and cost effectiveness to provide for a sustainable economic development. Energy demand management should thus help in

- planning for the future requirement, identifying conservation measures
- identification and prioritization of energy resources, optimized energy utilization, strategies for energy efficiency improvements
- framing policy decisions
- identification of strategies for reduced emission
- Energy models are developed using macro economic variables to forecast the energy demand. This helps in planning and drafting policies for energy management on the demand side.

3. Energy models

Energy models are developed for sustainable progress of any nation. Energy demand models can be classified in several ways such as static versus dynamic, univariate versus multivariate, techniques ranging from times series to hybrid models. Reviews of research done during the eighties and nineties are presented by Bohi [2], Bohi and Zimmerman [3] and David Wood Memorial Issue [4]. Chang et al. [5] reviews the production and consumption of both the traditional and the renewable energy in China over the past three decades. A review of energy management software tools are analysed to study the features of the tools in integrating renewable energy into various energy systems [6]. A review on the various optimization methods has been carried out by Baņos et al. [7] for optimum utilization of renewable energy sources.

Chen and Kung [8] have presented on how the forecasting accuracy can be improved by integrating qualitative and quantitative forecasting approaches. Energy demand is forecast using qualitative approaches such as survey whenever there is a dearth of information or when the end users perception, awareness and acceptance are required. The energy consumption pattern of households in different urban development forms is examined for Bandung City, Indonesia. A survey is conducted to determine the energy consumption patterns [9]. Liu et al. have used a survey to determine the household energy consumption pattern for a county in Tibet [10].

Energy forecasting models are developed specific to a nation or utility depending on the economic and market conditions prevailing. Baines and Bodger have adopted market forecasting approach for energy demand analysis. Energy accessibility and energy substitution are dealt with [11].

The Integrated Energy Planning Model (IEPM) is a technical and economic forecasting model. It is based on a detailed breakdown of energy consumption and energy transformation sectors. In this paper detailed analysis is presented for industrial sector. The main objective of the model is to balance energy supply with energy demand. The model considers variables such as: GDP growth rate and GDP structure, population growth rate, urbanization rate, number of households and industrial product share. The model presents various scenarios [12]. Unido's energy model consists of three sequential phases (i) analysis at aggregate level of current and future national energy matrices (ii) analysis of perspectives for decreasing energy intensity (iii) analysis of perspectives for increasing the supply and cost efficiency of sustainable (renewable) energy sources. The model is examined for China's energy situation [13].

Conditional demand analysis (CDA) is used to model the residential end-use energy consumption in Canada. The results are compared with neural network and engineering based models. The comparison of the predictions reveals that CDA is capable of accurately predicting the energy consumption [14].

The Integrated Energy System (IES) developed at Honeywell Prague Laboratory integrates all forms of cooling, heating, power generation, combined heat and power and cogeneration technologies. The system consists of a forecasting and optimization

mechanism. The forecasting module estimates the demand and the optimization module optimizes the load among the various production units [15].

A model is developed for Japan that simulates nationwide energy consumption of the residential sector by considering the diversity of household and building types. The model is used to develop scenarios and project the energy requirement in the residential sector [16]. Hu et al. present an Economy–Energy–Electricity–Environment (E4) framework [17]. It examines the strategy for low carbon and also presents China's economy growth, energy–electricity demand, renewable power generation and energy conservation and emissions mitigation until 2030.

Energy models are developed for sourcewise analysis – for oil, gas, electricity. Natural Resources Canada (NRCan) has used Oil and Gas Supply Model (OGSM) to predict the oil and natural gas supply and demand for Canada. The various parameters considered in the model include investment ratio, oil ratio, cost of oil reserves, oil prices, oil supply/production [18]. A technical and economic planning model (MIPE – Integrated Energy Planning Model) is used to estimate natural gas demand in three scenarios – low growth, high growth, sustainable development in four applications areas – industrial, electric power generation, domestic distribution, domestic distribution and vehicular fleet conversions [19]. A system dynamics model is used to forecast the growth of natural gas consumption. It is found that natural gas will become an important substitution for coal [20].

Electricity demand models are developed to study short term, medium term and long term load forecasting as well as for electricity demand country wide. A belief network model is used for forecasting the demand and required generating capacity of electricity. A dynamic simulation algorithm is applied to the belief network to take into account the feedback effects of decision [21]. Long term electric energy demand is determined using dynamic simulation theory by Jia et al. [22]. Social, economical and environmental factors are found to affect the electricity consumption. This results in seasonal, monthly, daily and hourly variations in electricity consumption pattern. Macro economic decision making is applied for electricity requirement forecast. By clustering the primary data and removing the periodic variance the complicated pattern is decomposed. Simple models are then applied and the electricity requirement is forecast [23].

Decision drivers for electricity demand and supply are identified for China. The framework consists of technological and socio-economic drivers, including those affecting electricity demand namely economic growth, structure, energy efficiency, urbanization, and change in per capita income and electricity supply namely deregulation, initiatives to promote natural gas, nuclear and renewable energy, air pollution regulations, price developments for coal and natural gas, and changes in generation technology [24]. The primary energy requirement is forecast for three scenarios – business as usual, conservative and optimistic by quantifying the above parameters [25].

Coarse modelling is used to develop a three stage electric energy load forecasting model to predict the yearly, weekly, hourly electric energy demand [26]. The model involves a stage wise prediction process (nested) involving analytical models. The manner by which hybrid renewable energy systems (HRES) can be commercially utilized for power generation in remote locations is examined by Deshmukh and Deshmukh [27]. Several HRES configurations such as PV–battery, PV–diesel, wind–battery, wind–diesel, PV–wind–battery, and PV–wind–diesel–battery are analysed and found to be commercially viable.

The review of energy demand forecasting models presented in this paper is categorized under broad headings as follows:

i. Time series models
ii. Regression models
iii. Econometric models
iv. Decomposition models
v. Cointegration models
vi. ARIMA models
vii. Artificial systems – Experts systems and ANN models
viii. Grey prediction models
ix. Input–output models
x. Fuzzy logic/Genetic algorithm models
xi. Integrated models – autoregressive, Support vector regression, Particle swarm optimization models
xii. Bottom up models – MARKAL/TIMES/LEAP

3.1. Time series models

Time series models are the most simplest of models which uses time series trend analysis for extrapolating the future energy requirement. Bargur and Mandel have examined the energy consumption and economic growth using trend analysis for Israel [28]. Gonzales et al. have forecast energy production and consumption in Asturias-Northern Spain [29]. A semi statistical cyclic pattern analysis is used for forecasting the primary energy demand for Turkey. The results are found to be similar to Winter's exponential smoothing technique [30]. Hunt et al. investigated the energy demand in sectoral basis for the UK using time series approach [31]. Three time series models, namely, Grey-Markov model, Grey-Model with rolling mechanism, and singular spectrum analysis (SSA) are used to forecast the consumption of conventional energy in India. Grey-Markov model has been employed to forecast crude-petroleum consumption while Grey-Model with rolling mechanism to forecast coal, electricity (in utilities) consumption and SSA to predict natural gas consumption [32].

Sourcewise analysis is also carried out to determine the future demand. The consumption of oil and price is forecast under three scenarios: Parabolic, linear and chaotic behaviour [33]. Aras and Aras [34] used the first-order autoregressive time-series model to predict the natural gas requirement for Eskisehir.

Load forecasting of electric energy demand has been examined by several researchers. In short term forecasting ranging from an hour to over a week, temperature, humidity along with past consumption is considered for demand projection [35–38]. Medium-term forecasts are usually for a week to a year. Researchers who worked on medium term load forecast include Abdel-Aal and Al-Garni [39], Barakat [40] and Wills and Tram [41] have worked on long term forecast.

The potential of using simple logistic curves for forecasting electricity requirement sectorwise is analysed for New Zealand [42]. Electricity demand for India is predicted using time series models [43]. A time-series-based decision support system that integrates data management, model base management, simulation, graphic display, and statistical analysis to provide near-optimal forecasting models for electricity peak load forecasting in UAE is developed. The model base includes a variety of time-series techniques, such as exponential smoothing, Box–Jenkins (BJ), and dynamic regression [44].

Gonzalez-Romera et al. [45] used trend extraction method to examine the electric energy consumption for Spain. In the field of interval time-series (ITS) forecasting, different techniques have been developed. Arroyo et al. [46] have developed three exponential smoothing methods for ITS forecasting.

Himanshu and Lester [47] have used time series analysis for predicting electricity demand in Sri Lanka. Electrical power requirement for Jordon is predicted using models that account for trend, monthly, seasonal and cyclic dynamics [48]. Amarawickrama and Hunt [49] have presented a time series analysis of electricity

demand in Sri Lanka. Various time series estimation methods were used to analyse using past electricity consumption. They have used income and price elasticities to predict the future electricity consumption in Sri Lanka.

Technology diffusion models such as Bass, Gompertz, Logistic, Pearl are used for projecting the energy demand for irrigation water pumping in India. The renewable energy distribution source-wise in the total energy scenario is determined based on the four models [50]. Pearl or logistic function is used to forecast the future wind energy patterns in India and in five states of India [51].

3.2. Regression models

Energy forecasts are very important in the framing of energy of environment policies. Regression models have been used to forecast the coal, oil, gas, electricity requirement [52,53]. O'Neill and Desai [54] analyse the accuracy in the projections of US energy consumption presented by Energy Information Administration (EIA). GDP and energy intensity (EI) are used in the projection of energy requirement. It is found that the GDP projections are consistently too high while EI projections are consistently too low. This tends to underestimate the future energy consumption. Linear and nonlinear effect of energy consumption on economic growth for Taiwan is examined by Lee and Chang [55]. It is found that a threshold regression provides a better empirical model than the standard linear model.

Regression models are also used for electric load forecasting – short term electric load forecasting [56–59] and long term electric load forecasting [60].

Jannuzzi and Schipper [61] have examined the of electrical energy consumption for the residential sector in Brazil. It was found that the increase in electricity demand was faster than the income. Dynamic relationship between electricity consumption and weather, price, and consumer income are examined by Harris and Lon-Mu [62] using 30 years data series from south east USA. Electricity demand based on the intensity of consumption is developed [63,64] to predict the future requirement.

The influence of economic variables on the annual electricity consumption in N. Cyprus is examined [65]. Using multiple regression analyses, the relationship between energy consumption, the number of customers, the price of electricity and the number of tourists is determined. A linear regression model was used [66] to predict the electricity consumption for Turkey based on the population and percapita consumption rates. Tunc et al. [67] used the regression analysis to predict Turkey's electric energy consumption.

Bessec and Fouquau [68] have examined the non linear relationship between electricity demand and temperature in the European Union. A panel threshold regression with exponential and logistic functions is considered for the data collected from 15 European countries. An empirical model based on multivariate regression is developed [69] to predict the electricity requirement of Jordon's industrial sector. Industrial production outputs and capacity utilization were found to be two most important variables that affect electrical power demand. The residential and commercial sector electricity consumption pattern in Hong Kong was examined [70]. Principal component analysis of five major climatic variables—dry-bulb temperature, wet-bulb temperature, global solar radiation, clearness index and wind speed—was conducted. It was found that sector-wide electricity consumption correlated with the corresponding two principal components determined using multiple regression technique.

A non parametric regression model [71] is used to assess the wind energy forecasts. The conditional price distribution is found to be non Gaussian. The forecasting models for electricity spot prices for which parameters are estimated by a least squares technique will not have Gaussian residuals.

3.3. Econometric models

Econometric models correlate the energy demand with other macro-economic variables. Samouilidis and Mitropoulos [72] have studied energy and economic growth in industrialized countries. Econometric models are developed to forecast energy consumption as a function of GNP, energy price, technology, population for India [73–75]. Ramaprasad Sengupta [76] and Rao and Parikh [77] have established that such models are effective in forecasting energy patterns in developing countries.

Arsenault et al. [78] have predicted the total energy demand as a function of previous year's energy demand, price of energy, real income and heating day for the province of Quebec. Ordinary least square technique (OLS) is used and prediction is made sector-wise – residential, commercial, industrial and street lighting. Yearly data has been used for demand side projection. Energy forecast is influenced by weather conditions data.

Energy supply and demand for the Asia-Pacific region is analysed [79]. The demand is forecast for three scenarios – high, low, base case considering variations in economic performance, prices and fuel substitution at the national and regional level. Four factors are considered for each country – econometric factors (GDP, foreign trade) with oil prices, domestic oil prices, substitution. A bottom up country by country approach is followed. Oil, natural gas, coal and electricity requirements are projected. The effect of price elasticities, income elasticities and technical efficiency on residential energy demand is studied for OECD countries using econometric energy models [80]. The energy requirement and CO_2 emission for Greece is forecast using econometric models. Demand equations are derived for each sector of economic activity traded, non-traded, public and agricultural sector and for each type of energy – oil, electricity and solid fuels. The energy system is integrated so that all interactions between energy, prices and production factors are considered [81].

Sharma et al. [82] analysed the requirement of three major forms of commercial energy in the state of Kerala (viz electricity, petroleum products and coal). Sectorwise/productwise econometric demand models are generated using regression method. ZhiDong [83] has conducted an econometric study for China linking energy, economy and the environment. A three equation model [84] is used for energy modelling and forecasting energy demand in UK and Germany. An economic model considers the price of electricity, oil, gas, coal, total energy demand and technological progress. The statistical model has the economic model embedded in its equation along with the error correction term. The results from the two models are then processes for structural change and stability.

Energy consumption in industrial, transportation, residential and commercial is determined for China using the consumption of fuel in a sector taking the case of a well off society [85]. Sectoral energy related parameters are identified to determine the final energy consumption in the sector. Econometric modelling is used for energy forecasting. Rural, social and economic data is collected for six provinces in China [86]. A sectoral energy demand analysis and a forecasting model are developed. Variables such as GDP, per capita income, agricultural production output, industrial production output, capital investment are used.

A modified form of econometric model EDM (Energy Demand Model) is used by Gori and Takanen [87] to forecast the Italian energy consumption. The possible substitution of various energy resources is investigated. In addition, the long term electricity consumption pattern in Italy is examined using cointegration and stationary time series models. The primary energy demand in Japan is determined by exploring the relationship between energy

demand, GNP and real energy price [88]. The resulting econometric model is used to determine long run price elasticity and income elasticity. The model is utilized to forecast the energy consumption and CO_2 emission.

Raghuvanshi et al. [89] determine the characteristics of the drivers of energy development for India. The primary energy consumption is decomposed as a product of three variables, population, per capita GDP and energy intensity of GDP. Similarly the CO_2 emissions are decomposed as the product of the primary energy consumption and the carbon intensity of primary supply. Ramanathan [90] has used data envelopment analysis to analyse the patterns of efficiency in terms of world energy consumption, Gross Domestic Product (GDP) growth and CO_2 emissions. The impacts of the changes in energy prices due to deregulation of prices is examined [91] on aggregate energy intensity and coal/oil/electricity intensity is studied. Price elasticities by energy type are determined.

The levels and types of demands for energy services in 2040 for Australia are determined by projecting the levels of economic activity [92]. Demand for 2040 is estimated by examining how energy intensity has been changing in each sector in recent years and this is used to project the future energy requirement. The changes in energy price elasticity and elasticities of substitution are examined [93] between energy and non-energy (capital and labour) sectors in China. It is found that accelerated market oriented reforms lead to energy efficiency improvements because the energy price elasticity declines, and elasticities of substitution and cross price elasticities between energy, capital and labour rise. An econometric model is developed to predict China's energy demand [94]. The energy requirement is forecast and an energy balance is presented for 2020 for China.

Bhattacharyya and Timilsina [95] have stated that basically two types of approaches namely econometric and end-use accounting are normally used in energy demand models. Lescaroux [96] presents a regional and sectoral model of global final energy demand. The main end-use sectors of consumption (industrial, commercial and public services, residential and road transportation), per capita demand is expressed as an S shaped function of per capita income. The effect of variables like energy prices, temperatures and technological trends are also examined. The model is applied on a panel of 101 countries. China's energy intensity is decomposed [97] to find the driving force that is increasing the energy intensity. A two stage approach with factor cost function and fuel share equations is used to determine the elasticities of substitution and price elasticities for interfactor substitution and interfuel substitution.

Econometric models are developed to forecast energy demand sourcewise – coal, oil, electricity and sectorwise – industrial, transport, residential for Korea [98] and for Nepal [99].

The IEA and DOE projections are used to determine the coal demand of China [100]. The paper indicates that even with conservative assumptions about Chinese GDP and income elasticity of electric demand, the coal demand in China will be high and consequently the CO_2 emission.

A modified logit function model is used for extrapolating crude oil and natural gas demands for France [101]. Population and GDP/capita are considered in forecasting the demand. A similar model is developed for Denmark [102].

Elkhafif [103] presents an iterative econometric technique for energy forecast which corrects the abnormal weather conditions data. The model is applied for sectoral natural gas sales data for the province of Ontario, Canada. The study reveals that residential and commercial natural gas data require more weather correction than the data for the industrial sector. Eltony [104] has used econometric models to examine the natural gas demand in Kuwait.

Econometric models are developed for the various petroleum products and natural gas for India [105]. Variables such as GDP/capita, population, price are considered to forecast the demand.

Logistic curve function is used predict the oil demand by considering consumption per capita against GDP per capita [106]. The IEA projections to 2030 for the OECD countries show no reduction in oil demand on a per capita basis. Historical data for China is projected using least squares technique. The results indicate that IEA's oil forecast has been underestimated. Transport energy demand is forecast for China using Partial Least Square Error (PSLE) method based on gross domestic product (GDP), urbanization rate, passenger turnover and freight turnover [107]. Econometric model is used to model five most important crude oil products demand in Spain [108]. The elasticity of demand is determined. It is found that the main factor driving demand is real income with prices having little impact on energy consumption.

Econometric models are used for electricity demand analysis. Liu et al. [109] have used econometric model to forecast electricity consumption and has compared the results with a neural network model. Logistic function is used to predict the electricity demand in Greece [110]. The correlation of gross domestic product, investments and relative electric price on demand is also examined.

Regression and correlation analyses are carried out for Hong Kong [111] to investigate the relationships between residential electricity consumption, economic variables and climatic factors. The seasonal and the yearly electricity use in the residential sector are forecast using the household income, household size, electricity price and cooling degree days. The econometric relationship between electricity consumption and income, price of electricity and diesel (used in for captive power generation to meet the shortages), and reliability of power supply from utilities in sectors namely residential, commercial, agriculture, small and medium industries, and large industries are examined for India [112].

Cobb–Douglas function is used for electricity demand projection for China with parameters – GDP, electricity price and autonomous energy efficiency [113]. The income and price elasticities are determined. An engineering and econometric model is used to predict the household electricity requirement for Norway [114]. The electricity consumption in New Zealand is forecast using economic and demographic variables [115]. Models are developed using multiple linear regression analysis with electricity consumption as a function of gross domestic product, average price of electricity and population. The model is validated by comparing the forecasts with those obtained using Logistic model.

In the context of climate change the future electricity demand is determined for Greece [116]. The electricity demand is determined using regression equation which considers population, GDP, energy intensity, monthly seasonality of electricity demand, monthly heating and cooling degree days. It is found that economic development has a strong effect on the future electricity demand. The electricity requirement in Italy is forecast using linear regression models [117]. The elasticities of GDP, price, GDP per capita for short run and long run and for domestic and non domestic electricity consumption are determined.

Two empirical models are developed based on multivariate linear regression analysis to identify the main drivers behind changes in electricity and fuel consumptions in the household sector in Jordan [118]. The results indicate that fuel unit price, income level, and population are the most important variables that affect demand on electrical power, while population is the most important variable in the case of fuel consumption. The relationship between electricity consumption and gross domestic product is examined for Malaysia using bivariate and multivariate models [119]. It is found that electricity consumption, real GDP and price share a long-run relationship.

The electricity consumption of China is forecast by categorizing the industry as primary, secondary and tertiary [120]. The annual electricity consumption is determined as a function of gross domestic product of primary industry, gross domestic product of secondary industry, gross domestic product of tertiary industry, consumption of rural household, consumption of urban household and consumption of government using partial least square method. Zachariadis [121] forecasts the electricity consumption of Cyprus using econometric analysis of energy use as a function of macro economic variables, prices and weather conditions. The research determines the future electricity demand in Europe using log-linear econometric model [122]. It also highlights how the electricity change impacts the climate, electricity costs including carbon costs.

3.4. Decomposition models

A list of 51 studies related to industrial energy decomposition are reviewed by Ang [123]. Two common approaches to decomposition are the energy consumption (EC) and the energy intensity (EI) approaches. In the energy consumption approach, the basic specified effects are associated with the change in aggregate production level, structural change in production, and changes in sectoral energy intensities, while in the energy intensity approach only the last two effects are considered. Relevant application issues, such as method selection, periodwise versus time-series decomposition, significance of levels of sector disaggregation, and result interpretation are reviewed in the paper. The decomposition of industrial energy consumption in Singapore at two levels of sector disaggregation is studied by Ang [124]. The impact of structural change and changes in sectoral energy efficiencies is examined for Singapore and Taiwan [125] by decomposing the industrial energy consumption. The decomposition is used to energy prediction.

A decomposition model is used for predicting aggregate energy demand in 15 European Union countries [126]. The model is decomposed into components to study the effect of sectoral energy intensity, structure change and GDP. The energy consumption and economic growth relationship is determined by examining how much of the variance in national income growth can be explained by the growth of different sources of energy consumption and employment in Turkey [127]. A generalized forecast error variance decomposition technique is used to determine the information content of the growth rate of energy consumption in Turkey.

The paper [128] applies an aggregate production function to examine the relationship among energy consumption, capital stock, and real income (real GDP per capita) in G-7 countries. Granger causality test, the generalized impulse response approach, and variance decompositions in a multivariate setting to determine the extent and the magnitude of the relationship among variables.

Decomposition models are also applied sourcewise – for oil, electricity. The studies carried out for oil, electricity are reviewed. Factor Decomposition method and System Dynamics (SD) modelling is used to predict the pattern of future oil consumption per capita (OCPC) [129]. Three factors were used for decomposition, i.e. economic activity, technological progress, and structure of energy consumption.

Short term load forecasting for Iran electricity market is done using singular spectral analysis (SSA) [130]. SSA decomposes a time series into trend and oscillation components. Simulation results show that the method gives better results.

Energy consumption pattern is analysed using fractional integration method. Gil-Alana et al. [131] have analysed the energy consumption by the US electric power by various energy sources using fractional integration. Research is carried out to test for long memory in disaggregated petroleum consumption in the United States using univariate and multivariate Lagrange Multiplier (LM) tests for fractional integration [132].

3.5. Unit root test and cointegration models

An econometric model of fossil fuel demand is determined for eight OECD countries, relating coal, oil and gas demands to GDP and prices [133]. In addition a model of endogenous technical progress has been estimated, aiming to include both price induced innovation in energy and structural change in the economy as long-term determinants of energy consumption. Cointegration and error correction model is applied to examine their relationships. Cointegration models were used with multivariate models to examine the influence of gross domestic product (GDP), income, degree-days, population, and energy price on energy demand in various countries by Dincer and Dost [134].

Johansen's multivariate cointegration tests preceded by various unit root or non-stationarity tests are used to test for cointegration between total energy consumption and real income of six Asian economies: India, Pakistan, Malaysia, Singapore, Indonesia and the Philippines [135]. A dynamic vector error-correction model is used to analyse the direction of Granger-causation and within-sample Granger-exogeneity or endogeneity of each of the variables. The relative strength of the causality is determined using the dynamic variance decomposition technique.

The disaggregated behaviour of UK energy crisis is examined [136]. The short and long run determinants of fuel demand, economic activity and real prices are examined. Cointegration analysis has been used to determine the longrun relationships; the residuals which are considered adjustments to the long run, has been fitted into an error correction model to determine short run elasticities. The researchers state that the real oil price is a major determinant of real national income and energy consumption for Korea [137]. It is also found that the combined effects of real money and real government expenditure on real income and energy consumption are also substantial for Korea.

Vector error-correction model estimation is used to examine the relationship between energy consumption and economic growth for Greece [138]. The vector specification includes energy consumption, real GDP and price developments – the latter taken to represent a measure of economic efficiency. The results indicate that there is a long-run relationship between the three variables, supporting the endogeneity of energy consumption and real output. The demand for the different types of energy consumption for Mexico is presented [139]. The Johansen procedure and the likelihood ratio tests are used to find the relationship between the types of energy and income. It is found that in Mexico the demand for energy is driven by income and relative prices. The stability between energy consumption and GDP for Taiwan is examined [140]. Aggregate and disaggregate data of energy consumption, including coal, oil, gas, and electricity, is used. Unit root tests and the cointegration tests allowing for structural breaks are performed on the data.

Al-Irian [141] examines the causality relationship between gross domestic product (GDP) and energy consumption in the six countries of the Gulf Cooperation Council (GCC). Panel cointegration and causality techniques are used to find the direction of energy – GDP causality in the GCC. Panel unit root testing procedure with multiple structural breaks is used to re-investigate the stationarity of energy consumption per capita across regions of the world [142]. The cointegration between energy consumption and GDP are analysed for Turkey [143]. The short term variation is predicted using a vector error correction model (ECM). The causality between variables is determined using the Granger causality model.

The energy imports in China is increasing at an enormous pace because of extensive energy consumption. China's energy import demand is predicted using cointegraiton and vector error correction (VEC) model techniques [144]. The paper examines the dynamic causal relationships between energy consumption,

emissions and output for France using cointegration and vector error-correction modelling techniques [145]. The relationship between energy consumption and economic growth is examined for China using cointegration and VEC approach at both aggregated and disaggregated level [146]. The relationship between energy consumption structure, economic structure and energy intensity in China is examined [147]. Cointegration, causality tests and VEC model have been applied to the energy data for China.

The energy consumption in China is forecast as a function of population growth, economic growth and urbanization level. Autoregressive distributed lag (ARDL) cointegration approach is used to find the long run relationship between urbanization process and energy consumption [148]. Unrestricted error correction model (UECM) is applied. The specification of the Granger causality test will be a vector autoregression (VAR) in first difference form. Factor decomposition model is used to find the changes in total energy consumption (direct and indirect) through its own key elements.

An empirical model of renewable energy consumption for the G7 countries is developed [149]. Panel cointegration estimates show that in the long term, increases in real GDP per capita and CO_2 per capita are found to be major drivers behind per capita renewable energy consumption. The intertemporal causal relationship between energy consumption and economic growth in Tanzania is examined [150]. The auto regressive distributed lag (ARDL) is used for the two types of energy consumption data, namely total energy consumption per capita and electricity consumption per capita. Causality tests are also conducted to find the causal flow.

The causal relationship between energy consumption and economic growth in three sub-Saharan African countries is examined [151]. Using the ARDL-bounds testing procedure, the causality between energy consumption and economic growth are determined. The unit root null hypothesis is performed on the energy consumption data for Australian states and territory [152]. The causal relationship between carbon dioxide emissions, energy consumption, and real output within a panel vector error correction model for eleven countries of the Commonwealth of Independent states is examined [153]. The impact of growth, energy and financial development on the environment in China is analysed using Autoregressive Distributed Lag (ARDL) cointegration approach [154]. The long run equilibrium relationship between financial development and environmental pollution is examined.

The impact of trade on energy consumption in a sample of 8 Middle Eastern countries using the panel cointegration data estimation techniques is examined [155]. Granger causality tests are conducted to determine the causality dynamics existing among the variables. The long-run relationship between energy consumption and real GDP including energy prices for 25 OECD countries is investigated [156]. The cointegration model indicates that international developments dominate the long-run relationship between energy consumption and real GDP. Energy consumption is found to be price-inelastic. Causality tests indicate the presence of a bi-directional causal relationship between energy consumption and economic growth. The causal relationship analysis between Gross Domestic Product, Energy Intensity and CO_2 emissions in Greece using Johansen cointegration tests and Granger causality tests based on a multivariate Vector Error Correction Modelling is studied [157].

Cointegration and error correction analyses have been extensively adopted in the study of energy demand sourcewise. Stock Watson dynamic (DOLS) and error correction modelling approaches have been used for estimating the demand for coal in China [158]. Cointegration and error correction method is used to find the short run and long run price and income elasticities. Long-run structural relationships of coal demand with price and income variables for the four major coal consuming sectors in India are analysed using cointegration model [159]. The models have been estimated using cointegrating VAR framework, which allows for endogeneity of regressors. The paper estimates the demand for gasoline in Kuwait using a cointegration and error correction model (ECM) [160]. Gasoline demand is inelastic with respect to price in the short and long run, while it is elastic in the long run. Gasoline demand is inelastic with respect to income in the short run. The relationship between gasoline demand, national income and price of gasoline is empirically examined using cointegration and error correction techniques for India [161].

The short run and long run effects between oil consumption and economic growth in China is explored [162]. Cointegration tests suggest that these two variables tend to move together in the long run. Granger causality test indicates oil consumption could be a useful factor to forecast changes in the economy both in the short and in the long run. The results indicate economic growth can be used as a predictive factor to predict oil consumption in the long run.

The future demand for petroleum products in India is studied [163]. Cointegration and error correction modelling approach is used. The long term demand elasticity for petroleum products is also determined. The demand for imported crude oil in South Africa is studied as a function of real income and the price of crude oil [164]. Johansen cointegration multivariate analysis is performed to find the long run relationship with income and price. The short-run dynamics are estimated by specifying a general error correction model.

Gallo et al. [165] Q15 uses unit root tests with two endogenous breaks to analyse the characteristics of oil prices, production, and consumption for several countries. By taking into account structural breaks, the relationship between oil consumption and oil prices is examined. Causality tests are also performed to determine the direction of any possible relationship between oil price and oil consumption and production for Organisation for Economic Co-operation and Development (OECD) countries.

Cointegration models are used to study the relationship between electricity demand and economic variables for Kuwait [166]. Co-integration techniques are used in the analysis of short and long-run effects of economic variables on energy use for US residential electricity demand [167]. An error correction model is also applied on the data. Ranjan and Jain [168] have studied the cointegrating relationship for electrical energy consumption in Delhi. Econometric models are used to investigate the determinants of electrical energy consumption in post-war Lebanon [169]. The impact of the Gross Domestic Product, total imports and degree days on electricity consumption is examined. Cointegration analysis is performed. Error correction models are applied. Statistical performance measures such as mean square error, mean average deviation and mean average percentage error are determined to validate the models.

The relationship between electricity consumption, employment and real income is examined using a cointegration and causality framework for Australia [170]. It is found that electricity consumption, employment and real income are cointegrated. Using cointegration analysis and autoregressive integrated moving average (ARIMA) modelling, the electricity demand is forecast for Turkey [171]. The projections are compared with government based projections and analysed.

Electricity consumption and its interaction with income, prices and the weather in the residential and the services sectors in Cyprus have been examined [172]. The analysis was done using time series techniques such as unit root tests with and without a structural break in levels, cointegration tests, Vector Error Correction models, Granger causality tests and impulse response functions. Cointegration analysis is carried out between electricity consumption and GDP for China [173]. Granger causality and Hodrick–Prescott

(HP) filter are applied to analyse the data for its directionality and decomposition.

Electricity consumption in G7 countries is determined using the panel unit root and panel cointegration techniques [174]. The model presents the long-run and short-run income and price elasticities for residential demand for electricity in G7 countries. The model is used to curtail residential electricity demand and to curtail carbon emissions in the long run. The cointegration analysis is also performed for 30 OECD countries by Narayan and Prased [175].

The causal relationship between electricity consumption and economic growth for Lebanon is examined using cointegration and Granger causality models [176]. Empirical results of the study confirm the absence of a long-term equilibrium relationship between electricity consumption and economic growth in Lebanon. Odhiambo [177] has examined the causal relationship between electricity consumption and economic growth in South Africa. The employment rate as an intermittent variable in the bivariate model between electricity consumption and economic growth is formulated. This results in simple trivariate causality framework.

Inglesi [178] examined the disaggregated behaviour of UK energy crisis. The short and long run determinants of fuel demand, economic activity and real prices are examined. Cointegration analysis has been used to determine the longrun relationships; the residuals which are considered adjustments to the long run, has been fitted into an error correction model to determine short run elasticities. Lai et al. [179] have investigated the causal relationship between electricity consumption and economic growth in a gaming and tourism centre in China. The gross domestic product is co-integrated with quarterly electricity consumption. Vector error correction (VEC) models indicated a lack of short-run relationships but showed that there was a long-run equilibrium relationship between electricity consumption and gross domestic product.

The increase in economic growth and energy demand has led to increased utilization of renewable energy especially in developing countries. Two empirical models for renewable energy consumption and income for a panel of emerging economies are presented [180]. Panel cointegration estimates indicate increases in real per capita income have a positive and statistically significant impact on per capita renewable energy consumption.

3.6. ARIMA models

ARIMA models have been extensively used in energy demand forecasting. A decision support system for forecasting fossil fuel production is developed using regression, ARIMA and SARIMA method for Turkey [181,182]. The method integrates each model by using certain decision parameters related to goodness-of-fit and confidence interval, behaviour of the curve, and reserves. Different forecasting models are proposed for different fossil fuel types. The prediction is made sourcewise – oil, natural gas, hard coal, lignite, wood, hydropower, petrocoke, plantain remains, geothermal heat, solar, asphaltite, geothermal electricity, primary energy.

Erdogdu [183] has estimated short and long-run price and income elasticities of sectoral natural gas demand in Turkey. The future electric energy demand is forecast using ARIMA. Short term electric load is forecast using ARIMA transfer function model [184].

A hybrid model with AR(1) and a finite impulse response filter is used for forecasting Lebanon's electricity demand [185]. The model is compared with autoregressive and ARIMA models and it is found that the hybrid model gave higher accuracy. Conejo et al. [186] have used ARIMA to forecast electric price while Pappas et al. [187] have used ARIMA to study the electricity demand load.

Sumer et al. [188] have used three models namely ARIMA, seasonal ARIMA and regression model to predict the electricity demand and have concluded that regression model with seasonal latent variable gave better result. Tourism-induced electricity consumption is studied for Balearics Islands, Spain [189]. ARMAX and GARCH models are applied to examine the daily electricity demand and the effect of tourism.

3.7. Expert systems and ANN models

In the past, expert systems and neural networks were being used extensively for electricity load forecasting. In recent times, it is also being used for long term energy demand projections considering macro economic variables. Neural network is used to model the energy consumption of appliances, lighting, and space-cooling in Canadian residential sector [190]. The energy consumption for Turkey is predicted using artificial neural-network (ANN) technique [191]. Two models are used: population, gross generation, installed capacity and years are used in the input layer of the network for Model 1 and other energy sources are used in input layer of network for Model 2.

Researchers have argued that green energy can be considered as a catalyst for energy security, sustainable development, and social, technological, industrial and economic development. The paper analyses the world green energy consumption through artificial neural networks (ANN). The world primary energy consumption including fossil fuels such as coal, oil and natural gas is also considered [192]. Sectoral energy consumption in Turkey is determined using ANN [193]. The model is then used for greenhouse gas prediction and mitigation.

Sözen and Arcaklioglu [194] have used three different models to train the ANN. In Model 1, energy indicators such as installed capacity, generation, energy import and energy export, in Model 2, GNP was used and in the Model 3, GDP was used as the input in ANN. The output of the network is net energy consumption (NEC). It is found that the ANN approach presents greater accuracy when economic indicators namely GNP, GDP are used for prediction. The energy demand for South Korea is estimated using a feed forward multilayer perception, error back propagation algorithm [195]. The model considered gross domestic product, population, import and export. The results are compared with the multiple linear and exponential regression energy demand models.

Pao [196] examines the following linear models: the exponential smoothing model (Winters), the exponential form of the generalized autoregressive conditional heteroscedasticity (EGARCH) and seasonal EGARCH (SEGARCH) models, the combined Winters with volatility EGARCH model (WARCH) and ANN non linear model. Based on the above models, two hybrid non linear models SEGARCH – ANN and WARCH – ANN are developed to predict Taiwan's consumption of electricity and petroleum. The models are validated using root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The results indicate the hybrid models give better accuracy and among the hybrid models WARCH-ANN is the better model.

The extent to which an economy relies upon imports in order to meet its energy needs is defined as Energy dependency (ED). Turkey's energy dependency is determined using ANN based on basic energy indicators and sectoral energy consumption [197]. Two models have been used. In Model 1, main energy indicators such as total production of primary energy per capita, total gross electricity generation per capita and final energy consumption per capita were used in the input layer of the ANN while sectoral energy consumption per capita was used in Model 2. A global optimization method called "Modal Trimming Method" is used to identify the values of model parameters [198]. In addition, the trend and periodic change are removed from time series data on energy demand. The converted data is used as the main input to a neural network. Furthermore, predicted values of air temperature and relative humidity are considered as additional inputs to the neural network, and their effect on the prediction of energy demand is investigated.

The Greek long-term energy consumption is predicted using ANN multilayer perception model. The input variables chosen are yearly ambient temperature, installed power capacity, yearly per resident electricity, consumption, gross domestic product [199]. Energy consumption in Turkey is modelled based on socio-economic and demographic variables (gross domestic product-GDP, population, import and export amounts, and employment) using artificial neural network (ANN) and regression analyses. The models are validated using relative errors and RMSE [200].

Neural Networks is used to predict the oil and natural gas consumption. Gorucu and Gumrah [201] have used ANN to predict the gas requirement for Ankara. GNP, population and vehicle kilometre are used as input parameters in training neural network model for predicting the transport energy demand for Turkey [202]. The best network architecture is selected using the training and validation data set. The final network is tested using the test data. The transport energy consumption in Thailand is determined using the national gross domestic product, population and the numbers of registered vehicles as independent variables [203]. Log-linear regression models and feed-forward neural network models are used in the study.

Neural Network models have been extensively used for short term load forecasting for electricity [23,204–238]. Several researchers have worked on NN models for medium term load forecasting [239–245] and also long term load forecasting [246]. Xia et al. [247] have used NN to forecast short, medium and long term load forecasting.

Wavelets are also used for short term load forecasting [248–250]. Benaoudaa et al. [251] have used wavelet based nonlinear multiscale decomposition model for electricity load forecasting. Adaptive wavelet neural network model is used for forecasting short term electric load with feed forward neurons [252].

ANN is used to forecast regional peak load planning for Taiwan [253]. The daily electric load profile is forecast using a combined approach of unsupervised and supervised neural network [254]. Kohanen's self organising map is used during the unsupervised stage. The neural network is trained using climate data along with historical load data to find the influence of climate variability. The model is validated to give good accurate results for short term load forecasting problem. The power distribution load is forecast using neural network for short term and medium term load in Nigde, Turkey [255].

Researchers have also used neural network to forecast electricity price. Gareta et al. have used a neural network model is used to forecast short term hourly electricity price [256] while Amjady [257] has used a neuro fuzzy approach to forecast electricity price.

Pao [258] has forecast the electricity requirement for Taiwan using nonlinear ANN and linear models – multiple log-linear regression (LNREG), response surface regression (RSREG), and regression with ARMA errors model (ARMAX) models. Four economic factors namely the national income (NI), population (POP), gross of domestic production (GDP), and consumer price index (CPI) are used to study its influence on the electricity consumption. Maia et al. [259] have used auto regressive moving average models (ARMA) with neural network and Maia et al. [260] present models for interval valued time series forecasting based on AR, ARIMA and Artificial Neural Networks.

Hamzacebi [261] used ANN to estimate the net electricity consumption of Turkey on sectoral basis while Sozen et al. [262] have used ANN to forecast sectoral energy consumption and greenhouse gas emission and discussed on consequent mitigation policies for Turkey. Gonzalez-Romera et al. [263] used neural network approach to forecast the trend and monthly fluctuation of electric energy demand. The monthly electric demand for Spain is analysed and a hybrid forecasting model is proposed [264]. The periodic behaviour is forecast using Fourier series function and the trend is forecast using a neural network.

Azadeh et al. [265] have used ANN for forecasting the annual electricity consumption in high energy consuming industries in Iran. The ANN approach is based on a multilayer perception model. The accuracy of the ANN results over regression models are validated using ANOVA. Midterm load forecasting of power systems is performed using a preforecast model (NN) and a hybrid model (neural network and evolutionary algorithm) [266].

The electricity consumption in the Asian gaming and tourism centre – Macao SAR, People's Republic of China is determined using multiple regression, artificial neural network (ANN) and wavelet ANN [267]. Five factors, namely temperature, population, the number of tourists, hotel room occupancy and days per month, are used to characterize Macao's monthly electricity consumption. The models are compared for their accuracy using mean squared error (MSE), the mean squared percentage error (MSPE) and the mean absolute percentage error (MAPE). It is found wavelet ANN is best among the models to forecast the electricity consumption.

Regression analysis, decision tree and neural networks are modelled using SAS Enterprise Miner for the prediction of electricity energy consumption in Hong Kong [268]. The decision tree and neural network models appear to be viable alternatives to the stepwise regression model in understanding energy consumption patterns and predicting energy consumption levels. The monthly electric power demand per hour is forecast in Spain for two years using two approaches – vector autoregressive (VAR) models and internal multi layer perception model (iMLP) [269]. The authors have concluded that for electric power demand forecasting for Spain iMLP has given better accuracy.

Meteorological and geographical data is fitted into an ANN model to determine the solar-energy potential in Turkey [270]. Scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms and a logistic sigmoid transfer function have been used in the network.

3.8. Grey prediction

Grey prediction gained popularity in the past decade because of its simplicity and ability to characterize unknown system by using a few data points. Energy demand forecasting can be regarded as grey system problem, because a few factors such as GDP, income, population are known to influence the energy demand but how exactly they affect the energy demand is not clear. Grey forecasting consists several forecasting models of which GM(1,1) is commonly used for forecasting. Grey relation analysis was used to predict the motor vehicular energy consumption in Taiwan [271]. The relative influence of the fuel price, the gross domestic product, the number of motor vehicles and the vehicle kilometres of travel (VKT) per energy increase are evaluated.

Energy consumption in China is forecast using grey prediction model which incorporates genetic algorithm [272]. A grey based cost efficiency model is used for optimal forecasting of power generation cost of renewable energy technologies [273]. The model quantifies the influences of cost reduction in power generation. Grey prediction model (GM) to predict and explore the dynamic relationships between pollutant emissions, energy consumption, and the output for Brazil [274]. In the long-run equilibrium emissions appear to be both energy consumption and output inelastic, but energy is a more important determinant of emissions than output. The causality results indicate that there is a bidirectional strong causality running between income, energy consumption and emissions. The GM model is compared with ARIMA model for validation.

The trend in the number of motor vehicle, vehicular energy consumption and the resulting CO_2 emission in Taiwan is studied using the grey prediction model [275].

Grey prediction model is used for electricity demand forecasting [276,277]. A taguchi method was used to optimize the parameter settings for the grey based electricity demand predictor [278]. The system when used in conjunction with a PC based electricity demand control system was expected to reduce the usage of electricity. A grey prediction model with trignometric residual modification is used for forecasting electricity demand in China [279]. The authors state that the model has improved the prediction accuracy to a large extent.

Grey prediction with rolling mechanism (GPRM) approach is used to predict the total and industrial electricity consumption in Turkey [280]. The results are compared with the energy prediction studies obtained using Model of Analysis of the Energy Demand (MAED). GPRM is found to have better prediction accuracy. Two models are developed. GDP and price elasticities are initially used to estimate nonresidential short run electricity for Romania [281]. A Holt–Winters exponential smoothing method and a trigonometric grey model with rolling mechanism (TGMRM) is then used for nonresidential electricity prediction. The results of the two models are then compared.

Grey prediction analysis is also used for prediction of renewable energy sources. Grey relative analysis and prediction is carried out for biofuels consumption on rural household in China [282].

3.9. Input–output models

An input–output model is used to assess how social and economic changes will affect energy requirements and energy intensity in China [283]. Six scenarios were developed by introducing major impact factors, such as technological advancement, population, income, and urbanization, in the input–output model to project China's energy requirements. Liang et al. [284] divided China into eight economic regions. A multi-regional input–output model for energy requirements and CO_2 emissions in China was established. Scenario and sensitivity analysis for each economic region is performed. The indirect energy consumption in the households of China is evaluated using an input–output model [285]. The indirect energy consumption of both rural and urban households is determined. Using the economic data, the input–output model is used to evaluate how the alternative energy policies impact production prices, consumption prices, and real income of rural and urban households through the mechanism of indirect energy consumption.

A growth model is integrated with an input–output model to analyse the impacts of economic growth on the energy consumption in Brazil [286]. Renewable and nonrenewable energy are considered. He et al. [287] have forecast the energy demand using the input–output table for Liaoning province in China. Scenarios are developed for three cases. Energy intensity and energy efficiency are considered in demand projection.

An input–output table of electricity demand (IOTED) is developed for China based on the input–output table of national economy (IOTNE) [288]. The electricity demand in various sectors is determined using the IOTED. Electricity demand multiplier (EDM) is used to identify dominant sectors that has a high electricity demand. Alcántara et al. [289] have developed an input–output table to study the electricity consumption pattern in Spain. The table helps in effective utilization of electricity by increasing energy efficiency.

3.10. Genetic algorithm/fuzzy logic/neuro fuzzy

3.10.1. Genetic algorithm

In recent years soft computing techniques are being in energy demand forecasting. Ceylan and Ozturk [290] have used genetic algorithm to estimate the energy demand for Turkey using economic indicators namely gross national product (GNP), population and import and export amounts. They established that the genetic algorithm (GA) model gave better accuracy as compared to the government's model. Genetic algorithm demand estimation models (GA-DEM) are developed to determine the future requirement of coal, oil and natural gas in Turkey based on population, gross national product, import and export [291].

Haldenbilen and Ceylan [292] have used genetic algorithm to estimate the transport energy demand in Turkey. Ozturk et al. [293] used the Genetic Algorithm EXergy consumption model (GAPEX) for predicting the petroleum exergy demand. Transport energy in Turkey is determined using meta-heuristic harmony search algorithm – HArmony Search Transport Energy Demand Estimation (HASTEDE) considering population, gross domestic product and vehicle kilometres as input [294]. Linear, exponential and quadratic models are used in the HASTEDE methodology. Optimum values are determined using sensitivity analysis (SA). A logistic based method is used to forecast the natural gas consumption for residential and commercial sectors in Iran [295]. Two methods are used to estimate the logistic parameters – one using nonlinear programming (NLP) and the second using genetic algorithm (GA).

Modern computational techniques using genetic algorithms are being adapted for load forecasting [296]. Tzafestas and Tzafestas [297] have used computational intelligence techniques for short term electric load forecasting. Ozturk et al. [298] used GA for forecasting the electricity energy demand of Turkey. The electricity consumption is determined based on gross national product, population, import and export data. Two different non-linear estimation models are developed using GA. The models are validated using actual data.

Azadeh and Tarverdian [299] present an integrated algorithm for forecasting monthly electrical energy consumption based on genetic algorithm (GA), computer simulation and design of experiments using stochastic procedures. Time-series model is developed as a benchmark for developing the GA and simulation models. ANOVA is used to validate the results. Considering electricity consumption, GNP, primary energy consumption, installed capacity, population, a neural network is designed which is improved upon using Genetic algorithm for the prediction of hydroelectric power in Turkey [300].

3.10.2. Fuzzy logic

Fuzzy logic is used for short term electric load forecasting [301–305]. Pai [306] has used hybrid ellipsoidal fuzzy systems while Ying and Pan [307] have used adaptive network based fuzzy inference system to forecast regional electricity loads.

The short term gross annual electricity demand for Turkey is forecast using fuzzy logic methodology [308]. GDP based purchasing power parity was the only parameter used in the model. The model is validated by comparing the forecasts with regression based forecasts and MENR projections (MAED).

Short term electric load forecasting has been predicted using neuro fuzzy system [309,310]. Padmakumari et al. [311] have forecast long term distribution demand using neuro fuzzy computations.

3.11. Integrated models – Bayesian vector autoregression, support vector regression, particle swarm optimization models

Some of the latest techniques such as Bayesian vector autoregression, support vector regression, ant colony, particle swarm optimization models are being used in energy demand analysis. A review of a few studies related to energy demand analysis is presented.

3.11.1. Bayesian vector autoregression (BVAR) model

Bayesian vector auto regressive model is used to predict energy requirement for China [312]. The primary energy requirement of coal, oil, gas, hydro is projected till 2010. A Bayesian Vector Autoregression (BVAR) model and Granger-causality are applied to study growth in energy demand and the relationship between energy consumption to real gross domestic product per capita in selected few Caribbean countries [313]. The increased growth in energy consumption indicate the need for long-term commitments to undertake a series of economic, market, and research and development measures to advance the adoption and deployment of new energy technologies. Bayesian neural network approach is used for short term electric load forecasting [314,315].

3.11.2. Support vector regression

Fan et al. [316] and Hong [317] have used support vector model electricity load. Electricity consumption is derived as a function of socio-economic indicators such as population, gross national product, imports and exports [318]. SVR (support vector regression) was created for each of the input variables to predict the electricity consumption for Turkey. RMSE was used to find the best e-SVR model for each variable. Moving average and e-SVR (support vector regression) are used to forecast the short term electricity demand. ANOVA is used to validate the accuracy of forecast obtained by comparing its results with ARIMA model [319].

3.11.3. Ant Colony Optimization (ACO)

The energy demand in Turkey is determined using Ant Colony Optimization (ACO) [320] with independent variables such as gross domestic product (GDP), population, and import and export amounts. Toksari [321] again used ACO technique for forecasting Turkey's electricity energy demand.

3.11.4. Particle swarm optimization (PSO)

Particle swarm optimization (PSO) based energy demand forecasting (PSOEDF) is used to forecast the energy demand of Turkey [322]. Gross domestic product (GDP), population, import and export are used as energy indicators of energy demand. The results are validated by comparing with the ant colony optimization (ACO) technique performed for energy demand estimation. El-Telbany and El-Karmi [323] have used PSO for short term forecasting of Jordon's electricity demand.

A particle swarm optimization method is used for annual peak load forecasting in electrical power systems [324]. Actual recorded data from Kuwaiti and Egyptian networks are used. The model is validated using least error squares estimation technique.

3.11.4.1. Hybrid models. The review states that SVR with genetic algorithm and SVR with simulated annealing are superior to other competitive forecasting models. However genetic algorithm (GA) and simulated annealing (SA) algorithm loses the previous knowledge of the problem once the population (GA) or the temperature changes (SA). Chaotic particle swarm optimization algorithm is used in the SVR for electric load forecasting model. The results indicate that the above model gives better accuracy than GA or SA algorithm [325].

A new combined model for electric load forecasting based on the seasonal ARIMA forecasting model, the seasonal exponential smoothing model and the weighted support vector machines is used for electric load forecasting [326]. The model is found to effectively map the seasonality and nonlinearity normally present in the electric load data. The adaptive particle swarm optimization is used to optimize the weight coefficients in the combined forecasting model.

The paper presents an SVR-based electric load forecasting model that applied chaotic ant swarm optimization (CAS) technique, to improve the forecasting performance [327]. The CAS combines with the chaotic behaviour of single ant and self-organisation behaviour of ant colony. The empirical results indicate that the SVR model with CAS (SVRCAS) performs better as compared to SVRCPSO (SVR with chaotic PSO), SVRCGA (SVR with chaotic GA), regression model or ANN model.

3.12. Bottom up models – MARKAL/TIMES/LEAP

3.12.1. MARKAL

The MARKAL (acronym for MARKet ALlocation) is a bottom-up, dynamic technique which was originally developed as a least cost linear programming model by the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency. The equations for the initial MARKAL model are given by Fishbone and Abilock [328]. Numerous improvements have been made in the model for in depth analysis [329–331].

The MARKAL model depicts both the energy supply and demand sides of the energy system. It is an analytical tool that can be adapted to model different energy systems at the national, state and regional level. MARKAL model is used to study the impact of policy changes. Carbon mitigation strategies can also explored using the model. Scenarios are developed using the 'what if' framework [332,333]. As of 2005, Loulou et al. [334] have documented that MARKAL and TIMES models have been used in more than 80 institutions in 50 countries for various purposes including economic analysis of climate policies.

The MARKAL model is used for Shanghai to develop scenarios during various policy conditions. The study analyses how the air pollutant emission can be reduced using the MARKAL model when different policy decisions are taken and also the benefits that accrue by mitigating the increase of CO_2 emissions is also explored [335–341].

Analysis for 2003, 2007 and the regulatory impact assessment of the Climate Change Bill were undertaken using the UK MARKAL and MARKAL – Macro (M-M) energy–economic models by Strachan et al. [342]. To achieve 60% CO_2 reduction, a range of scenarios focusing on energy supply, technology pathways and macro-economic cost implications are presented. MARKAL model is used to model the UK residential energy sector with an objective of reaching a target of a 60% reduction in carbon dioxide (CO_2) emissions by 2050 [343].

MARKAL model is applied to allocate various energy sources across sectors in India for Business As Usual (BAU) scenario [344]. The paper analyses the sectoral energy consumption pattern and emissions of CO_2 and local air pollutants in the Kathmandu Valley, Nepal using MARKAL model [345]. The paper also presents various scenarios for emission reduction.

The drivers for increased utilization of natural gas is identified using the economic optimization model MARKAL [346]. The drivers are identified to be government mandates of emissions standards, reform of the Chinese financial structure, the price and supply of natural gas, and the rate of penetration of advanced power generation systems.

3.12.2. TIMES G5 model (the integrated MARKAL–EFOM system)

Long term energy demand and CO_2 emission for China is forecast using TIMES G5 model. Sourcewise and sectorwise energy demand are determined using the key indicators such as population, GDP, person-km, GDP per capita, heating per capita, cooking per capita, heating per GDP, cooling per GDP [347].

3.12.3. LEAP

The Long-range Energy Alternatives Planning system (LEAP) model was developed by the Stockholm Environment Institute at Boston (SEI-B). It is a bottom-up-type accounting framework which

is used for forecasting. The LEAP Model also has been developed to model the energy needs at the national, state and regional level Lazarus et al. [348].

Energy demand and supply are calculated for different Mexican end-use sectors based on the data from the national energy balance [349]. The transformation programme simulates the energy demand in terms of electricity generation and distribution, natural gas, oil and coke production, etc. Based on the energy requirements calculated in the demand analysis programme the primary energy supplies in transformation programme are matched with the energy demand.

In 1997, SEI-Boston along with five leading international research and training institutes – EDRC (South Africa), ENDA (West Africa), ETC (Europe), FAO-RWEDP (Asia), IDEE (Latin America) – joined to create a new suite of tools for integrated energy-environment analysis. This was funded by the Netherlands Ministry of Foreign Affairs (DGIS). The LEAP 2000 was designed to cater to the needs of energy planners and policy makers. The model can be used to study the effect of introducing strategies, greenhouse gas mitigation assessments for sustainable energy development. LEAP 2000 is a scenario-based energy-environment modelling tool. Its scenarios are based on a comprehensive accounting of how energy is consumed, converted and produced in a given region or economy under a range of alternative assumptions including population, economic development, technology, price, etc.

LEAP model has been used for energy systems planning at country level – US Country Studies program (USCS) [350], Mexico [351], China [352], Taiwan [353], Rawalpindi and Islamabad [354].

LEAP has also been used for sector-level analysis: in electricity generation [355], in electricity generation for China [356], transportation [357,358], household [359], in household sector in Delhi [360]. Other studies about bioenergy scenarios have been reported for Vietnam [361], Korea [362] and biofuels for Mexico [363].

Kadian et al. have used LEAP system for modelling the total energy consumption and associated emissions from the household sector of Delhi, India [360]. Energy consumption under different sets of policy and technology options is analysed. The LEAP model is applied for long term forecast of Taiwan's energy supply and demand, the greenhouse gas emission. Scenarios are developed for various case situations [353]. The LEAP model was used to estimate total energy demand and the vehicular emissions in Rawalpindi and Islamabad [354]. LEAP system software is used to study the potential effects of electric trolley bus system in Kathmandu Valley [364]. The fuel consumption and greenhouse gas emissions are projected till 2025.

LEAP model is used to predict the electricity requirement for China [356]. Three scenarios are developed and CO_2 emission level is determined. To combat the CO_2 emission which is expected to triple or quadruple various structural adjustments in the electricity sector is suggested such as demand side management, circulating fluidized bed combustion. Islas et al. [363] have used the LEAP model for Mexico to find the feasibility of using biofuels in the transportation and electricity generation sector. Their impact on the Mexican energy system is analysed. Future scenarios based on moderate and high use are developed. It also evaluates the efficient use of biofuels in the residential sector, particularly in the rural sub-sector.

4. Conclusion

Energy demand forecasting models for commercial and renewable energy have been reviewed. It is found that every nation is interested in detailed energy planning for its sustained development. Energy intensity is being determined to find the relative energy utilization by a nation. The econometric models indicate that GNP, energy price, gross output, population are being linked to energy demand. Technological development, energy efficiency are also linked to the energy demand in econometric models. Decomposition models highlight the strength of the macro variables with energy demand with reference to a certain nation. Cointegration models and causality tests indicate the direction of the causal variables with reference with energy demand. It is found that ARIMA models are linked with neural networks and other soft computing techniques to improve the accuracy of energy demand forecasting. Grey prediction is yet another technique being tried successfully for energy demand analysis. Genetic algorithms, fuzzy logic, SVR, AGO, PSO are emerging techniques in forecasting commercial and renewable energy sources. It is found that the models link energy, economy and environment for planning the future energy utilization in a sustainable manner. It is expected that such models will help energy planners to accurately plan for the future and utilize the sustainable and renewable energy resources to a larger extent. The models will facilitate policy makers and administrators to take decisions for a greener tomorrow. The review indicates that macro economic energy modelling is vital for every nation. Sophisticated modelling techniques such as grey prediction, genetic algorithms, fuzzy logic, SVR, AGO, PSO can be used by researchers for macro energy economic planning for accurate energy demand prediction.

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